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Applied Artificial Intelligence in Manufacturing and Industrial Production Systems: PEST Considerations for Engineering Managers

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***Index Terms*—Artificial intelligence, engineering management, industrial production, manufacturing, PEST analysis.**

***Abstract*—Presently, artificial intelligence (AI) is playing a leading role in our contemporary world via numerous applications. Despite its many advantages, analytical frameworks highlighting the implications of AI applications are still evolving. Particularly, in manufacturing and industrial production where novel technologies are continuously being harnessed. Consequently, AI and the implications of its applications have relatively remained a grey area for many engineering managers who are key players in the gravitation of manufacturing and industrial production towards the fourth industrial revolution and more recently, the fifth industrial revolution, generally termed as Industry 4.0 (I4.0) and Industry 5.0 (I5.0), respectively. In this study, the implications of AI applications in the general context of manufacturing and industrial production, are presented to provide insight for engineering managers. These implications are discussed via PEST (political, economic, social, and technological) considerations of the broad implications of the adoption of AI techniques in manufacturing and industrial production systems. A new engineering management model has not been proposed in this paper. Rather, a discussion aimed at serving as a tool for the appraisal of the implications of the general applications of AI by engineering managers, who may not be AI specialists or data science experts is presented.**

I. Introduction

Presently, digital technologies assisted by artificial intelligence (AI) techniques are at the core of many innovative solutions across several sectors. These sectors include engineering design, research and development, manufacturing, and industrial production [1]–[4]. With a focus on manufacturing and industrial production, a majority of new and emerging AI-based paradigms are mainly aimed at the robust analysis of data and elimination of repetitive jobs on the shop floor for advanced process automation and holistic decision-making. Generally, these fundamental aims can be viewed as the promoters or proponents of present-day industrial revolutions (i.e., the fourth industrial revolution (I4.0) and the fifth industrial revolution (I5.0)). Despite their interrelations in areas such as the use of big data analytics and AI-driven devices and systems, I4.0 tends to emphasize the digitization of manufacturing and industrial production to have better coordination between machines and information technology (IT), while I5.0 tends to focus on the introduction of human intelligence into I4.0 paradigms for closer collaboration between humans and machines in present and future smart manufacturing and industrial production systems [5].

AI is one of the emerging tools, perhaps, the most critical tool being used to drive I4.0 and I5.0, to facilitate improved efficiency and performance in manufacturing and industrial production [4], [5]. This is because the core components of I4.0 and I5.0, e.g., cyber-physical systems (CPSs), multi-agent systems and technologies, intelligent automation, predictive maintenance, and virtual technologies, all rely on AI techniques, especially AI-driven data-intensive algorithmic frameworks [4], [5]. As a result, present-day engineering managers are laden with not only an understanding of how AI techniques can be applied but how to thoroughly appraise managerial concerns that the applications of AI techniques may pose to manufacturing and industrial production. In other words, conventional engineering management in manufacturing and industrial production which tends to focus on the effective and efficient deployment of operational technologies and operational management, transitions into the inclusion of effective oversight of IT (information technology) operations and efficient deployment of data science modeling techniques. In this way, the span of control of engineering managers must accommodate new key players, particularly, data science practitioners. This is because AI techniques that can be feasibly deployed for manufacturing and industrial production to improve performance and ensure higher efficiency, often rely on data-driven algorithmic and modeling architectures and frameworks [6], [7].

To better understand why data science modeling techniques and frameworks are essential for the application of AI in manufacturing and industrial production, intelligent analytics (a core component of I4.0 and I5.0) can be considered [5]. Intelligent analytics is made possible through the deployment of AI techniques, particularly, machine learning techniques, and it is generally implemented in the form of predictive analytics [8]. It essentially describes a watchdog [8] – a service that evaluates the modi operandi of real-world devices and systems to ascertain their optimal functioning and utilization through continuous modeling and analysis of data (delivered mostly by sensors connected to machine tools and equipment) with advanced embedded systems. Aside from intelligent analytics and other glaring added advantages such as efficient automation and improvement of process control that data-driven

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models introduce to manufacturing and industrial production, extensive use of statistical and quantitative analysis, and explanatory and predictive modeling (all components of data analytics) also, is tantamount to fact-based management for informed decision-making and action plans in manufacturing and industrial production [9].

Despite the many advantages associated with the continuous and growing application of AI techniques in manufacturing and industrial production, specifically and generally [10], some cons remain. For instance, an autonomous robot designed and built for spray painting in car assembly plants may have its traditional functions extended for expedited color changeovers via AI techniques such as deep reinforcement learning [11]. However, to utilize such an augmented robot effectively and efficiently on the shop floor, typically, only one specialist (e.g., a robotic engineer or robotic system operator) is often required. This ultimately makes most, if not all, of the direct labor roles and manual activities previously associated with spray painting in the car assembly plants where such a robot is installed and utilized redundant. This scenario typifies one of the many scenarios that engineering managers may have to deal with as AI-driven technological advancements progressively orchestrate the full, and or, semi-automation of activities and processes; specifically, on the shop floors and generally, within manufacturing and industrial production facilities.

Another typical case of how the application of AI techniques can aid, and at the same time, present uncertainties in the engineering management workflow within manufacturing and industrial production facilities is detailed in [12]. In [12], to better understand the profitability of brick manufacturing relative to revenues from customers, clustering (a form of unsupervised learning [13]) is used to evaluate and draw inferences from manufacturing and sales datasets. Even though the outcomes presented in [12] provided apt details that may not have been otherwise available to the human decision-makers (e.g., manufacturing and production engineers, system operators, sales managers, and engineering managers) without the intervention of the AI technique adopted, the extrapolation of the outcomes from such an illative system is not always clear-cut. As a result, the formulation of action plans and the making of decisions based on such inferences may pose a challenge for engineering managers who will be saddled with this responsibility. This is understandable because engineering managers are not data scientists or data science experts, per se.

Compounding the challenge discussed above is the fact that efficient methods for data collection are not straightforward for many manufacturing and industrial production systems and processes [14]. For example, temperature regulation and monitoring of a manufacturing system or an industrial production process can be carried out using purpose-built temperature sensors. If it is required to build a database by generating datasets over the operational life cycle of the temperature sensors to undertake predictive maintenance as exemplified in [15], a sampling time (i.e., time interval) must be decided a priori for the generation of the data points or observations (i.e., temperature measurements from the temperature sensors). From a practical viewpoint, the time interval cannot be too small because this will lead to the generation of an overly large dataset, i.e., an over-complete representation of the temperature data, that will require a lot of computational resources for processing. In a similar vein, the time interval cannot be too large because this will lead to the generation of an overly sparse and less accurate dataset. Given this scenario, it can be inferred that the choice of the time interval introduces a trade-off and a very likely bias in the collection of data from manufacturing systems or industrial processes to drive data-driven AI implementation. Such a bias also needs to be understood by engineering managers, particularly, when techniques such as forecasting using time series analysis or time-dependent trend analysis are being utilized as core components of AI implementation.

Based on the discussions above, a study is undertaken in this paper to present the pros and cons of applying AI techniques in manufacturing and industrial production by providing insights to better inform and guide engineering managers through the use of a Political, Economic, Socio-cultural, and Technological (PEST, also referred to as STEP in literature [16]) analytical tool. Particularly, the following contributions are made:

- Discussion on the current political, economic, socio-cultural, and technological trends in the application of AI, including ethics and the risk assessment of AI-driven product innovation.
- Summarized checklist-based PEST-informed guideline for engineering managers to incorporate a knowledge base of data science into their decision-making and action planning for AI adoption.

Even though the discussion in this paper is not exhaustive, it is envisaged that it will serve as a precursor to subsequent generic and specific managerial discourses focused on the ever-evolving application of AI techniques in manufacturing and industrial production systems. The remainder of this paper is organized as follows: Section 2.0 provides an overview of PEST analysis, Section 3.0 discusses the implications (i.e., pros and cons) of applying AI techniques in manufacturing and industrial production systems using a PEST analytical framework, and the concluding remarks are given in Section 4.0.

II. PEST ANALYSIS

PEST analysis is a very popular methodology in management [17]. Generally, it describes the macro-environmental factors that are often considered in strategic management appraisal [18], [19]. When the conduct of PEST analysis is focused on business operations (e.g., manufacturing and industrial production processes), then it becomes a crucial part of the required evaluation for the implementation of strategic goals such as the short-term or mid-term, or long-term or recursive use of AI techniques in assisting manufacturing and industrial production. As a result, PEST analysis provides insight into the crucial factors that engineering managers must take cognizance of to guarantee the reliability of managerial decisions. Hence, its adoption in this paper.

The considerations stemming from the PEST analytical framework viewpoint, which engineering managers ought to

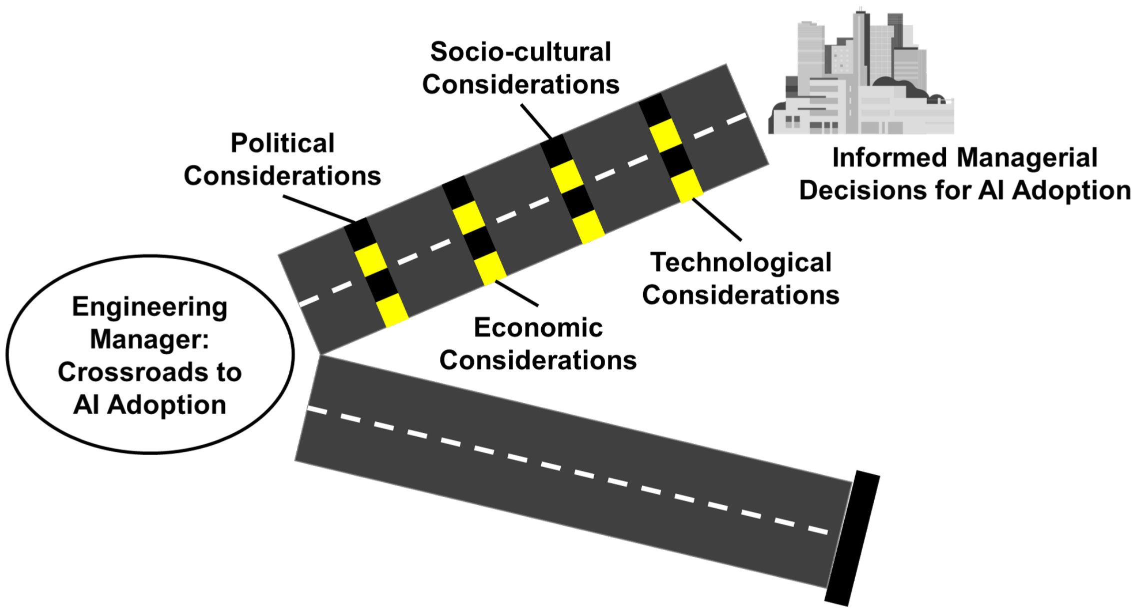

Fig. 1: Components of the PEST analytical framework.

address head-on to guarantee informed managerial decisions on the road to AI adoption are illustrated via a visual juxtaposition in Figure 1. It is envisaged that armed with the foreknowledge of AI adoption scenarios, based on these considerations, engineering managers are less likely to meet a dead end or hit a roadblock as they lead the course of AI adoption to facilitate I4.0 and I5.0. These considerations are discussed in the next section.

A summarized guide is provided in Table I in the form of nuggets that can facilitate PEST-informed AI adoption by engineering managers, who oversee manufacturing and industrial production. Even though the details in Table I are not exhaustive due to the dynamic and evolving nature of AI techniques that assist manufacturing and industrial production operations and processes, and the plethora of perspectives associated with them from different application viewpoints, the actions mapped against the PEST considerations in Table I provides the engineering manager with a good basis and simple tool for evaluating the pros and cons of AI adoption in manufacturing and industrial production systems.

III. Discussion

The PEST considerations introduced in Section II and summarized in Table I are further discussed as follows to provide engineering managers with more insight:

A. *Political considerations*

Even though AI is increasingly impacting business activities and technical operations in diverse industrial sectors and management disciplines, many of which directly or indirectly sway present-day governance, a well-established unified framework for the adoption and regulation of AI is still very much embryonic [20]. A lot of concerns have been identified when it comes to the disruptiveness of AI technologies and their ability and increasing potential to subtly dictate and engineer politically motivated outcomes [21]. For example, exploratory data analysis and big data analytics which are both components of AI have been deployed for targeted advertisements, misinformation, and disinformation [22]. Other seemingly disruptive use cases of AI-based digital technologies on political grounds include but are not limited to weaponized robots, drones, and long-range missile defense systems [23], [24]. There are several other use cases of AI-driven technologies that can inherently be swayed towards unethical “political” applications; however, potential cyberattacks and cyberwars, tend to be the most prevalent of all the politically motivated disruptiveness associated with the adoption of AI technologies.

AI-based digital and emerging technologies are mostly data-driven and implemented on software architectures. When deployed on manufacturing and industrial production systems such as supervisory control and data acquisition (SCADA) systems, AI-driven paradigms and software applications can become prone to malware such as Stuxnet [25]. Stuxnet and other forms of malware built to target manufacturing and industrial production systems are often politically motivated [26]. This fact was reinforced recently when the largest pipeline system in the United States of America (USA) experienced a service disruption due to a cyberattack [27] and the recent disruption of IT systems at multiple European oil facilities hit by cyberattacks [28]. Handheld and mobile devices such as tablets and personal digital assistants that now offer similar or the same functionalities as human-machine interfaces (HMIs) in manufacturing and industrial production [29], are also prone to contemporary spyware [29].

The trends discussed above strongly indicate that a unified framework in the ethical design, development, and deployment of AI technologies is very essential. To ensure robustness and reliability, such a unified framework must take into account data privacy and security. This is very essential for AI applications involving proprietary manufacturing and industrial pro-

TABLE I: Summarized guide for PEST-informed AI adoption in manufacturing and industrial production systems.

Factors	Recommended Actions
1) P - political considerations	• Conform current and potential AI applications to local, international, and organizational ethical and regulatory laws and standards. • Classify or categorize manufacturing and industrial production data required for current and potential AI applications into proprietary and non-proprietary in accordance with data privacy and security standards and regulations. • Identify specific and potential use cases and interested political and non-political parties or stakeholders for AI adoption. • Develop generic and specific organizational terms of reference for AI adoption by considering both local and global smart manufacturing and industrial production standards and align organizational AI-based data-driven frameworks with both local and global data handling and management policies. • For AI-generated products and services that are designated for non-civil applications such as military applications, national and international security policies, and military standards must be strictly adhered to throughout the production life cycle or the duration of service.
2) E - economic considerations	• Critically evaluate return on investment for current and potential AI adoption. • Develop holistic managerial models to handle disparities between economies relative to the geographical location of manufacturing and industrial production assets and facilities designated for AI-based augmentation. • Promote inter-organizational and intra-organizational economic knowledge sharing with respect to AI adoption. • Ensure organizational inclination to collaborative AI to guarantee a balanced transition from traditional workflows to AI-assisted workflows and to enhance operations and processes without overly impacting the need for experts in the labor force and human interaction. • Avoid the pitfalls of elitist markets through the classification of AI-generated products and services to accommodate a wider range of customers and their product and service requirements.
3) S - socio-cultural considerations	• Evaluate the potential impact of AI adoption on the restructuring and reorganization of both direct and indirect workforce in terms of job creation and job replacement for manufacturing and industrial production at the decision-making levels. • Ascertain the availability and affordability of the required specialized workforce for AI adoption based on demographics and location of industrial production and manufacturing facilities. • Ensure that AI adoption is ethical and does not infringe upon societal rights and cultural norms and values, as far as possible. • Model and implement technology acquisition (TA) and technology transfer (TT) programmes to ensure sensitization and readiness of the workforce for AI adoption. • Continuously improve on the organizational TA and TT models using current data/information to guarantee conformity to present socio-cultural realities.
4) T - technological considerations	• Appraise all application-specific scenarios for current and potential AI adoption. • Make a strong case for cybersecurity as traditional and legacy manufacturing and industrial production systems metamorphose into CPSs. • Conduct technological risk assessments to facilitate fail-safe methodologies prior to low-scale, medium-scale, and large-scale AI adoption for manufacturing and industrial production. • Ensure a good balance between minor investments in AI technologies to enhance operations and processes and major investments in AI technologies to drive innovation and profitability. • Understand and continuously evaluate the spectra of risk associated with generic and specific AI implementation and formulate metrics for key risk indicators across the board for manufacturing and industrial production activities.

duction data collection, visualization, and exploration. Even though governments, bodies, and organizations are taking giant strides in ensuring that the applications of AI technologies are within the boundaries of societal laws, it is very challenging to achieve robust monitoring and supervision of AI technologies due to the convergence of technologies involved and the ability of AI systems to evolve mostly through self-learning [30].

To buttress the point raised above, the example of autonomous drones that can be used for product delivery [31] or the bombing of target sites [32], depending on the payload and the data fed into it, can be considered. This and several other use cases validate the fact that the general ethical principle of designing and developing AI technologies is relatively the same. However, the data fed into AI systems to invoke various use cases are application-specific. This is the primary bottleneck of AI technologies. Who provides oversight into the data to be used and the applications to be built? This is a genuine query that engineering managers need to take into account and investigate going forward, whilst making a case for the adoption of AI technologies in manufacturing and industrial production systems via data-driven paradigms. Some recommendations are provided in Table I to guide engineering managers in this regard.

It is also good to note that in the last decade, several documents on AI ethics, policy, and governance have been produced, with over 80 produced in the last five to six years alone. Still, it can be argued that the discourse on AI ethics, policy, and governance remains a political hot potato even today. This is mainly because, AI, in and of itself, is always open to a plethora of views due to its inherent wide and varied applications. In the context of manufacturing and industrial production, the convergence of technologies, particularly, operational technology and information technology, has always played a huge role in the efficient automation of systems and processes on the shop floors and along production lines. As a result, established standards and regulations are in place to ensure proper installation, commissioning, operation, maintenance, and decommissioning of conventional industrial equipment and machine tools. With the introduction of AI (data-driven paradigms and algorithmic frameworks) into manufacturing and industrial production, new standards, and regulations such as ISO/FDIS 23704 (currently under development at the time of this research endeavor) [33] have to be put in place to take into account changes such as the transitioning of traditional machine tools and equipment into cyber-physically controlled smart machine tools and systems. It is the responsibility of engineering managers to be abreast of these developments regarding AI adoption as recommended in Table I.

B. Economic considerations

The current and future global economic impact of the applications of AI techniques in manufacturing and industrial production cannot be overstated. In [34], it is estimated that AI may deliver an additional economic output of around US $13 trillion by 2030. Interestingly, the projected time in [34] coincides with the set year for the consolidation of the sustainable development goals (SDGs) [35]. A survey covering the developed countries (USA, Finland, UK, Sweden, Netherlands, Germany, Austria, France, Japan, Belgium, Spain, and Italy) that jointly account for over 50% of the world's economic outputs hints that by 2035, AI applications will likely double annual global economic growth rates [36]. The forecasted growth rates in [36] are expected to trickle down to three major areas: the increase in labor productivity by 40% as a result of emerging and innovative technologies, the creation of a virtual workforce capable of problem-solving and self-learning via intelligent automation, and the convergence and diffusion of innovation across multiple sectors to generate new revenue streams. In seeming contrast to the projections in [34], it is estimated that AI technologies will contribute modest gains in the range of US $1.49 to US $2.95 trillion to the global economic output from their direct and indirect positive impacts on productivity, jobs, and gross domestic product (GDP) in [37].

As a building block for the emerging digitization of manufacturing and industrial production (i.e., I4.0 and I5.0), technologies such as the Internet of Things (IoT), cloud computing, 3D printing, robotics, augmented reality, big data analytics, and smart sensors may eventually see to the metamorphosis of manufacturing and industrial production into a single cyber-physical system (CPS) in which a convergence of the internet, digital technologies and, manufacturing and industrial production is realized [38]. Such systems which present unprecedented levels of automation are bound to eliminate (partially or totally), the requirement for direct manual labor inputs, leading to higher productivity. In this way, AI technologies will complement and assist the existing workforce of many industries and economies once the relatively huge initial capital investments in intelligent machines, software, and systems have been made. In other words, by adopting the enhanced automation and augmented intelligence provided by AI technologies, manufacturing, and industrial production tasks will be performed better and more efficiently in a highly reduced time.

Even though the economic advantages of adopting AI technologies in manufacturing and industrial production are obvious as discussed above, it is envisaged that many of the economic advantages to be offered by AI technologies will be maximized majorly by developed economies, particularly, North America, Europe, and Asia [34]. As a result, developing countries may only record very modest or little economic advantages due to lower rates of adoption of AI technologies. On this premise, it is intuitive to suggest that the varying levels of adoption of AI technologies will further widen the economic gap between advanced countries and lagging countries. This is yet another issue that engineering managers who are responsible for manufacturing and industrial production plants and facilities in both developed and developing countries must take into cognizance by adopting and implementing relevant AI policies and strategies that promote equity and continued knowledge sharing via technology transfers (TTs) and technology acquisitions (TAs) in the adoption of AI technologies. TT and TA are further discussed in the next subsection, and some recommendations are provided in Table I to guide engineering managers in this regard.

C. Socio-cultural considerations

Applications of AI techniques for manufacturing and industrial production continue to raise concerns around ethics, safety, and responsibility. Even though many of the AI techniques deployed as manufacturing and industrial production solutions do not necessarily operate fully autonomously, at the risk of repetition, it is good to note that the advent of AI has led to the automation of many manufacturing and industrial production operations and processes. For example, pick-place robot manipulators assisted by deep learning algorithms can potentially replace nearly all manual pick-and-place operations once carried out by humans on the shop floor [39]. Consequently, many industries can reduce manual labor costs by downsizing whilst retaining similar or higher levels of productivity. However, this may not be the case for industries located in less advanced societies, where both the capital and expertise to deploy digital technologies and AI solutions for manufacturing and industrial production are unavailable. This begs the question of the availability and affordability of AI solutions. The susceptibility of manufacturing and industrial production systems to failures or even complete blackouts as a result of corrupt data or malicious algorithms or even cyber-attacks is another critical issue that raises valid security concerns. It is envisaged that advanced countries that have access to state-of-the-art technologies will be better positioned to afford and deploy AI solutions while mitigating and responding to perceived risks or threats in comparison to developing or less advanced countries.

It must be noted that AI solutions are often software solutions or programs built on abstraction layers that can be interacted with via an application-layer interface (API) [35], somewhat similar to the open systems interconnection (OSI) model [40]. For typical manufacturing and industrial production solutions, a reduced OSI model [41], is preferred to ensure higher latency and faster computations as it is often required in safety-critical applications [42]. A reduced OSI model having a shorter stack is generally a simplification from the data network architecture and design viewpoint; however, this directly complicates the architecture and design of software services [41]. This is primarily because specialized workarounds will be required to achieve "higher layer-like" functionalities when applications directly drive layers close to the physical layer [41]. Such levels of expertise required for specific manufacturing and industrial solutions could be rare in many developing countries and even in some developed countries [43]. This is another challenge in terms of the equity of AI and its global outlook.

TA [44] and TT [45] models and programmes can adequately bridge the above inherent gaps in AI adoption in many developing countries and some advanced countries through a clear understanding of how socio-cultural variations (particularly, the level of specialized technical education of the populace) will impact planned TA and TT models and programmes. Such TA and TT models and programmes will ultimately yield a specialized AI-driven industrial workforce. Engineering managers ought to pay close attention to these dynamics that will ensue within the local and global industrial workforce for the adoption and implementation of AI technologies in manufacturing and industrial production. In this way, concerns about uneven competition, technology readiness, ownership, and responsibility, regarding AI adoption to drive business value and returns, can be better understood and measured multilaterally. Some recommendations are provided in Table I to guide engineering managers in this regard.

D. Technological considerations

Several digital and emerging technologies are currently being deployed in many manufacturing and industrial production processes. For example, the Coca-Cola company which is arguably the largest beverage company in the world, recently leveraged big data analytics to develop and market a new flavor (Cherry Sprite) [46]. The data used for the research and development was collected from the company's state-of-the-art of self-service soft drinks machines (fountains allowing customers to blend their personalized drinks) [46]. There are several other examples, such as the Coca-Cola case, where industries have deployed unprecedented data-driven AI models to rebrand their operations and products to drive innovation. Recently, Siemens, added a neural processing unit (NPU) to one of their robust programmable logic controller (PLC) modules, the SIMATIC S7-1500 PLC, to have SIMATIC S7-1500 TM NPU [47]. This augmentation allowed equipment or machines used for packaging to better recognize complex patterns through the hybridization of AI and vision technologies. Hence, improving the efficiency and robustness of the packaging process. This made the SIMATIC S7-1500 TM NPU the automation and controls product of the year in 2020 [47]. These use cases and several others reveal the growing impact digital and emerging technologies continue to have on manufacturing and industrial production systems and processes.

Whilst several subjects and disciplines focused on digital and emerging technologies are being incorporated into diverse engineering curricula and specialized training programmes [48], a clear rationale for making strong cases for best practices and standards for AI applications still seems to be lacking. This is primarily because the deployment of these technologies is often application-specific (as mentioned already in Section III-A), and there is no unified methodology for their appraisal. For instance, to remotely monitor a piece of industrial equipment via an online HMI, internet connectivity is often required as demonstrated in [49], [50]. As a result, the industrial equipment leaves a digital footprint that can be viewed or accessed illegitimately, if resilient firewalls and cybersecurity measures are not put into place. The tipping point with this scenario could be a malware or spyware attack on the industrial equipment as discussed in Section III-A. Hence, the augmentation of manufacturing and industrial production equipment via AI-based innovative technologies may also increase the vulnerability and susceptibility of such equipment to malicious attacks.

To avoid scenarios such as the one discussed above, engineering managers must have an insight into the modi operandi, vulnerabilities, and susceptibilities of AI-driven digital and emerging technologies before employing or deploying them for improved productivity and efficiency, and to drive innovation. Even though there are no fool-proof technologies, a thorough assessment of the vulnerabilities and susceptibilities of AI-driven technologies designated for assisting manufacturing and industrial production will equip engineering managers with fail-safe methodologies to mitigate and or respond to inherent and potential risks [51], that could emanate from adopting such AI-driven digital and emerging technologies. Also, since the application of AI techniques, in and of itself, can not adequately quantify and qualify inherent and potential risks associated with AI-driven technological innovations, robust methodologies such as risk matrices and real-win-worth (RWW) screens can be adopted conjunctively to better manage inherent and potential risks that such AI-driven technological innovations may be fraught with [52]. Some recommendations are provided in Table I to guide engineering managers in this regard.

IV. Conclusion

In this paper, PEST considerations for adopting and implementing AI in manufacturing and industrial production systems are discussed to provide a broader knowledge to engineering managers, to assist in the managerial decision-making process. Specifically, emphasis has been laid on what queries or concerns engineering managers need to be wary of if they are to make an informed case for the adoption of AI-driven technologies to assist manufacturing and industrial production. The paper also discusses the pros and cons of applying AI techniques within industrial production and manufacturing using some real-world manufacturing and industrial production contexts.

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